Modeling stochastic variability in accreting black holes

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and

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Outline

Introduction / Motivation Why variability?

Part 1. Stochastic model for the luminosity fluctuations *Kelly et al 2009, 2011, 2014.*

Part 2. Applications.

Fermi/LAT γ -ray blazar variability. Sobolewska et al 2014. ApJ, 786, 143 Radio-to- γ variability of 3C 273. Sobolewska et al 2014, in progress

Summary



Introduction. Variability

Variability is a probe of astrophysics

Variability properties reflect physics of the variability processes

X-ray variability process is multiplicative (Uttley+2005).

A tool to weigh BHs in AGN (X-rays, McHardy+2006).

Geometry of the X-ray emitting region (Kara+, Alston+, de Marco+).

Blazar emitting region (TeV, Aharonian+2007).

Classification of astronomical sources based on variability, in the era of massive time-domain astronomical surveys

Introduction. Variability

Non-parametric methods (PSD, structure function) suffer from distorting effects (e.g. Vaughan+2003, Emmanoulopoulos+2010) due to:

- the finite sampling of the light curve: red noise leak and aliasing
- irregular and/or sparse sampling

Monte Carlo simulations to calculate the expected periodogram as a function of the true underlying PSD (e.g. Done+1992, Uttley+2002):

- χ^2 minimization based methods

- computationally intensive

Likelihood based approaches

e.g. Kelly+2009, 2011, 2014; Vaughan 2010; Miller+2010

Advantages of our approach:

Parametrized stochastic process, PSD parameters derived directly from the lightcurve.

No spectral distortions due to irregular/sparse sampling, red noise leak, aliasing because the Fourier transforms are not performed. Model accounts for arbitrary sampling and observation lengths.

Bayesian approach, statistical inference based on **the likelihood function,** i.e., the probability of the measured lightcurve as a function of the PSD parameters.

posterior dist. of parameters given the data \propto Likelihood \times prior

Markov Chain Monte Carlo (MCMC) to sample from the posterior probability distribution for the model parameters, e.g. PSD characteristic timescales.

Ornstein-Uhlenbeck process, OU

Continuous time first order autoregressive process, CAR(1) Damped Random Walk, DRW



$$P_{\rm OU}(\omega) = \frac{\varsigma^2}{2\pi} \frac{1}{\omega_0^2 + \omega^2}$$

Application of the OU model to the optical AGN lightcurves

Kelly+2009: OU model explains the optical AGN lightcurves with an impressive fidelity. McLeod+2010: OU model used to describe the 10-year SDSS Stripe 82 AGN lightcurves. Kozłowski+2010: AGN selection based on the variability properties (OGLE).

Investigations into the adequacy of the OU model

Good agreement on timescales well sampled by the data (from months to a few years).

On very short timescales (below a few months) the optical PSD slopes steeper than predicted by the OU process (Mushotzky+2011, Kepler; Zu+2013, OGLE).

The OU process preferred over several other stochastic and deterministic models (Andrae+2013, SDSS Stripe 82).



Mixed OU process resulting in a PSD with two breaks.



Kelly+2011

"Py,

Test on the AGN X-ray data

Successful application of the mixed OU model to the X-ray RXTE (Sobolewska & Papadakis 2009) and XMM-Newton lightcurves of 10 nearby radio-quiet Seyferts.

Potentially the most precise method for estimating the BH mass in AGN, a tight anticorrelation between the amplitude of the driving noise fluctuations and the BH mass.





CARMA(p, q)

Continuous time autoregressive moving average process



CARMA(p, q)

Continuous time autoregressive moving average process

CARMA(1, 0) = CAR(1)



CARMA(p, q)

Continuous time autoregressive moving average process

Stationary CARMA(p, q) process: q < p and the roots r_k of the AR polynomial have negative real parts



PSD of a stationary CARMA(p, q) process is a sum of weighted Lorentzian functions with

centroids $\propto |\text{Re}(r_k)|$

widths $\propto |\text{Im}(r_k)/2\pi|$

normalizations $\propto \beta_i$

Part 2. Applications

OU/mixed OU process:

Variability of the Fermi/LAT γ -ray blazar lightcurves

CARMA process:

Radio-to- γ variability of 3C 273 (in progress)





Ghisellini 2013 (review)

The first 4 years of the Fermi/LAT survey data



Questions

- 1. Is the γ -ray blazar variability consistent with a stochastic process?
- 2. Are the 'flares' a signature of an additional variability process?
- 3. How do the γ -ray blazar variability timescales compare to the X-ray variability timescales?
- 4. Can we constrain the geometry of blazar γ -ray emitting zone?



Part 2. Applications. Fermi/LAT γ -ray blazars



Sobolewska+2014

The mixed OU model favored in 10 of 13 blazars





The OU model

Posterior probability distributions of the OU characteristic timescale



Sobolewska+2014

Summary

The Fermi/LAT γ -ray lightcurves of blazars consistent with the OU or mixed OU processes.

Characteristic time scales constrained in two BL Lac type sources. Limits derived for the remaining sources.

Constraints on the blazar PSD slopes.

Hints for a sub-hour scale blazar variability.

CARMA model - fast and flexible method of characterising AGN variability.

Insights into the **jet/corona** interplay (X-ray band) in 3C 273. Realistic estimate of broad band variability and its uncertainty on various time scales.

